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Market competition and strategic interaction in the Spanish FinTech industry

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ABSTRACT

Financial technology (FinTech) is driving innovation in the financial industry worldwide, but it also poses a threat to traditional banks by the new FinTech start-ups. This article contributes by analysing whether incumbent financial institutions, through their FinTech ventures, compete or collaborate with the new FinTech firms. As a case study, we use the emergent FinTech industry in Spain during the decade of 2010s – a country with a world-leading banking sector before the global financial crisis and now third in Europe by number of FinTech firms. Competition among FinTech firms is measured using the Herfindahl–Hirschman index, the Panzar-Rosse H statistic, the Lerner index, and the Boone indicator, while an oligopolistic conjectural variation model tests interaction between bank-owned and independent FinTech start-ups. The results show that traditional banks use their FinTech ventures to compete against the new players in the industry. The process has led to sharp reductions in concentration but moderate, albeit increasing, market competition in the context of a twentyfold increase in revenues during the decade. Authorities can draw lessons for policy-making in favour of regulation that promotes a level playing field in which independent FinTech start-ups can compete.

1. Introduction

The last decade witnessed the rise of FinTech as a global phenomenon. Information technology is driving innovation in the financial industry, both in terms of digitalisation and emergence of new competitors, for a total investment of USD 226.5 billion in 2021, ten times more than in 2013 (KPMG, 2022). The impact of this phenomenon on the banking industry is not obvious. On the one hand, new technologies improve banks' competitiveness by reducing operation costs, improving service efficiency, enhancing customer-oriented business models, and increasing risk-taking capabilities (Wang et al., 2021b; Zhao et al., 2023), so banks would see FinTech start-ups as collaborative suppliers in their value chain. On the other hand, FinTech start-ups may as well represent a threat to the incumbent

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banks, eating into banks' business and menacing their competitive leadership.[3] Empirical evidence of the negative impact of FinTech on bank performance include Gomber et al. (2017) and Phan et al. (2020), which motivated banks' reaction to invest in FinTech start-ups such as partnerships, service outsourcing, venture capital funding, and acquisitions (PwC, 2016; Hornuf et al., 2021), as well as launching their own FinTech projects (Lee and Shin, 2018).

A relevant question is henceforth whether banks will compete or collaborate with the new FinTech start-ups; that is, if we will observe a substitution effect and disruptive innovation or a complementary effect and collaborations (Li et al., 2017; Zveryakov et al., 2019). This also translates into the impact that digital finance has on broader social concerns, such as access to financial services by the most disadvantaged and higher levels of efficiency of the financial system in terms of faster transactions with reduced costs, among others. The motivation of this article is to delve into this question by analysing the degree of competition between two distinct groups of players in the FinTech industry: bank-owned FinTech ventures and independent FinTech start-ups. Indeed, FinTech firms owned by incumbent banks are expected to show different business operations, pricing behaviour and/or cost structure than their competitors, as being part of larger and well-established financial groups would provide them with access to larger amounts of customer data that may be converted into meaningful information for decision-making (Abedin et al., 2023).

To such purpose, we use the FinTech industry in Spain as a case study, with a twofold goal: to assess the degree of market competition in the industry over the past decade, and to derive to which extent the strategic interaction among the FinTech owned by incumbent banks and the independent FinTech firms explains competition. A key reason to choose this case study is that the Spanish banking industry was one of the world leaders until the global financial crisis hit hard, followed by the rise of a FinTech hub in recent years.[4] By 2020, Spain had 6% of the 3500 FinTech in Europe – in third place by number of firms (Deloitte, 2020) – despite being only seventh by level of consumer adoption of FinTech (EandY, 2021). Total investment in the industry amounted EUR 542 million in 2021, an increase of 151% compared to 2020, mainly in business-to-business service-oriented companies (Sánchez and Quintanero, 2022). Incumbent banks have made a significant investment effort, with a share in FinTech ventures valued at EUR 65 billion by end-2021.[5] However, most of this effort comes from BBVA and Santander's investments outside Spain, leaving the question open on whether banks are willing to compete or collaborate with local FinTech firms. Last but not least, a key reason to choose the Spanish industry is that all private firms must disclose their financial statements in accordance with the Spanish General Accounting Plan, which allows the study of market competition by considering firms of any size – something that would be unfeasible in countries such as US or Canada.

Our research contributes with an analysis of competition by payment services providers and lending companies in the Spanish FinTech industry during the decade of 2010s. First, concentration measures and indicators of market competition are used to evaluate how market structure evolved in the industry. This includes Herfindahl–Hirschman index, Panzar-Rosse H statistic (Panzar and Rosse, 1987), Lerner index (Lerner, 1934), and Boone indicator (Boone, 2008). We then use an oligopolistic conjectural variation model (Spiller and Favaro, 1984) to test competition between bank-owned FinTech ventures and independent FinTech firms, and explore whether incumbent banks use their ventures to compete or collaborate with the new entrants. We thus fill a gap in the literature, where there is hardly any research specifically oriented to the analysis of market competition and strategic interaction in the FinTech industry.

We obtain three main findings: First, industry revenues increased twentyfold during the period, with higher growth rates and sharp reductions in concentration after 2014. Second, the measures of market power show only moderate levels of competition in the industry, with a peak in 2015 according to the H statistic or with an increasing trend afterwards according to the Boone indicator and Lerner index. Third, instead, our conjectural model suggests that strategic interactions exist between FinTech firms owned by banks and the independent FinTech firms, with a clear pattern of competition, rather than collaboration, by the FinTech owned by banks. Hence, the implications for policy-making would favour a body of regulation that promotes a level playing field for independent FinTech start-ups. These results, however, could be conditioned by some limitations of our analysis, namely those due to the availability of financial data and some assumptions required to estimate both the industry output and marginal costs.

The structure of the article is as follows. Section 2 describes the conceptual framework, with a brief review of the literature of market competition and a closer look at the case study. In Section 3, the methodology and hypotheses to be tested are defined. The empirical analysis and the discussion of results are provided in two separate sections: Section 4 on indicators of market competition in the industry, and Section 5 on the analysis of strategic interaction among independent and bank-owned FinTech firms. Section 6 is devoted to the discussion of our results compared with other relevant studies. Finally, Section 7 concludes.

2. Conceptual framework and case study

In this section, we first provide an approach to our case study – the rise of the FinTech industry in Spain in recent years – and then describe the conceptual framework of our research with a review of the literature on models and indicators of market competition.

2.1. The emergence of the FinTech industry in Spain

The global financial crisis hit the Spanish banking industry hard, which since the 1990s had been a world leader (Kase and Jacopin, 2008; Santos, 2017), with strong rates of market penetration and at the cutting edge in technology (Bátiz-Lazo et al., 2011;

[3] See The Economist, May 2021: www.economist.com/special-report/2021/05/06/how-fintech-will-eat-into-banks-business
[4] Nasdaq.com, Jan. 2020: www.nasdaq.com/articles/whats-driving-spains-rise-as-a-fintech-hub-2020–01-29
[5] Expansión, Dec 2021: www.expansion.com/empresas/banca/2021/12/02/61a7f6f2468aeb9d488b45fb.html

Maixé-Altés, 2016). As shown in Fig. 1, the boom and bust of credit led to the complete restructuring of the industry after 2010, with the demise of most savings banks and the concentration of more than fifty banks into ten groups holding 80% of the assets (Peón and Guntín, 2021).

More recently, a new threat appeared at the national and international levels: the rise of FinTech firms. Their disruptive innovation challenges the incumbent banks in most of the traditional services they offer (such as means of payment, credit, investment vehicles and advisory services), with the provision of new services, and entering areas underserved by traditional banks (Jagtiani and Lemieux, 2018). We mapped the FinTech industry in Spain during the 2010s,[6] with a hand-collected list of brands in five market niches (some firms operating in more than one): neobanks and payment services, credit (personal and corporate credit, comparators, crowdfunding-lending), investment services (personal and enterprise financial management, trading, wealth management), insurtech (including comparators), and other financial services (including cryptocurrencies and blockchain, know-your-customer and security-identity-fraud services, and other services). Table 1 shows the number of FinTech firms with positive annual revenue, as well as the sum of total revenues in the industry from 2010 to 2019.

Our inventory is more complete than those by Spanish FinTech associations and existing academic taxonomies (e.g., Carbó-Valverde et al., 2020; Sánchez and Quintanero, 2022), as it identifies more than 600 brands, although many of them are inactive today. These brands are owned by about 480 companies, of which 395 have some financial information available in the Spanish commercial registry for the decade 2010–2019. While 309 of these firms were still active by the end of 2019, only 23 (102) had revenues above 10 million (1 million) euros. As shown in Table 1, the boom is clear, with a fivefold increase in the number of companies by the end of the decade and a tenfold increase in total revenues. The largest increase is observed in payment services, particularly in terms of total revenues, followed by the credit niche. By 2019, the two niches combined accounted for more than 80% of industry revenues (1.28 billion out of 1.57 billion euros),[7] with the number of firms increasing sevenfold and total revenues more than twentyfold.

Incumbent banks did not stand still. A dilemma in the industry was whether traditional banks and FinTech companies should compete or cooperate, particularly in the face of a major threat – the big tech companies. To illustrate, the CEO of BBVA pointed out: "banks need to take on Amazon and Google or die" (González, 2013). They had already been leaders in the digitalisation process, with the two largest banks using online banking brands since the early 2000s (Uno-e by BBVA and Openbank by Santander, both merged today with their respective owners).[8] And now, with the emergence of the FinTech firms, it is noticeable in Table 1 how the incumbent banks reacted after 2011, when Comercia Global Payments (payment institution of Caixabank, the third largest bank in Spain) started to operate. Since then, the FinTech firms owned by banks or allied to them increased market share from 30.8% in 2011 (70.0 billion in revenue out of total industry revenues of 227.2 billion) to 37.7% in 2015 (225.7 billion out of 598.9 billion), followed by a decreasing trend afterwards – mostly due to a boom of independent firms in the payment and credit segments.

Following the above, we choose to limit our research in time and space: we focus on payment services and lending FinTech, which are the bulk of the industry,[9] during the decade of 2010 s – before the impact of the 2020 pandemic, when a structural change is noticeable both in terms of GDP drop and the first increase in credit in more than one decade (see Fig. 1). We seek to measure the degree of market competition over time, to answer the research question of whether FinTech owned by incumbent banks engaged in strategic interactions that differ from those of the independent FinTech, explaining competition.

2.2. Literature review on indicators of market competition

The dynamics of industry competition can be analysed by means of different structural and non-structural approaches. The structural approaches are based on the structure-conduct-performance (SCP) paradigm, according to which the market structure of an industry is exogenous and influences firm conduct, which in turn influences its performance. In this sense, the relative-market-power hypothesis (Shepherd, 1982) states that firms with large market shares and differentiated products exercise market power and make higher profits. Simple indicators to assess market competition include the number of firms in the industry, measures of concentration ratio, and the **Herfindahl–Hirschman index (HHI)**.[10]

Alternatively, the efficient structure hypothesis (ESH) states that firms with superior management or production technologies have lower costs and therefore obtain higher profits (X-efficiency, Demsetz, 1973), whilst other firms produce at more efficient scales and therefore have lower unit costs and higher unit profits (scale-efficiency, Lambson, 1987). This results in firms having larger market

[6] The details of this compilation are provided in Section 4.

[7] Since some firms operate in more than one niche, the sum of revenues in all five segments is somewhat higher than the industry total. Thus, the 1.28 billion revenues of payment services and credit niches represent 81,1% of the total (1.57 billion), but 72.2% of the 1.77 billion revenues if niche overlaps are considered (see Table 1).

[8] Former digital banks by BBVA and Santander, Uno-e and Openbank, are not considered in this research. These were brands inside their respective group, consequently lacking separate financial information. Moreover, keeping them out of the study is consistent with the focus of the analysis, which is observing the incumbent banks' reaction to the financial disruption brought by the fintech firms after the global financial crisis, with the launch of new FinTech ventures or setting alliances with existing ones.

[9] Crypto and blockchain firms are not included inside payment services, as in many instances they belong to commercial applications such as exchanges for virtual currencies or cannot be disentangled from the use of crypto as an asset (Bott and Milkau, 2016). Moreover, we did not trace any of those firms to be owned by banks, which limits their interest for this research.

[10] The concentration ratio is the sum of the market share held by the largest specified number of firms in an industry. Instead, the HHI is expressed as the sum of squared market shares of all firms (Kvålseth, 2018).

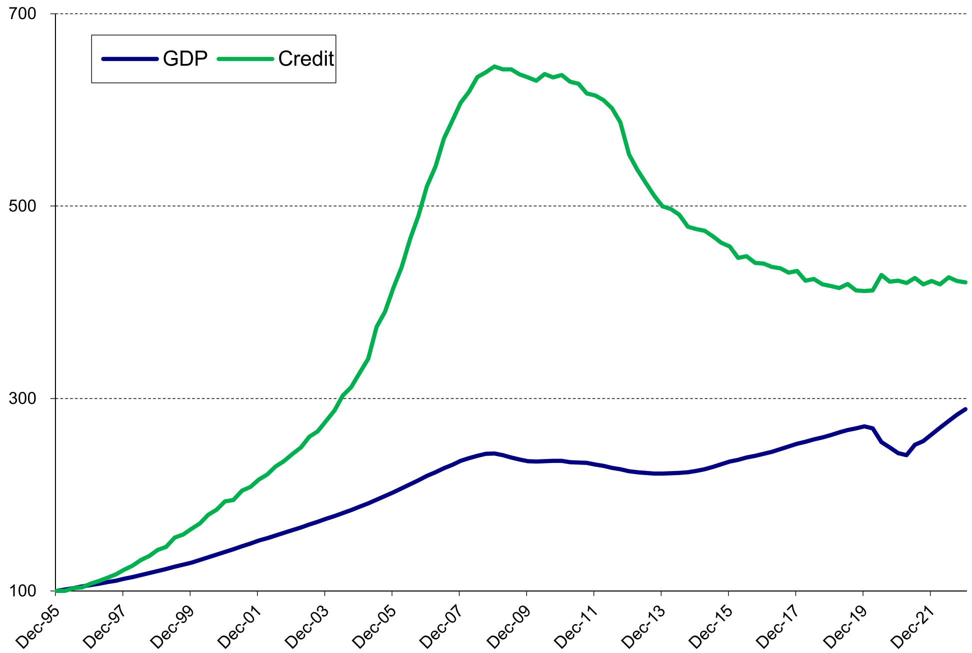

Fig. 1. Credit to households and firms in Spain, 1996–2022 (1996 base = 100). Source: Banco de España (BdE), Instituto Nacional de Estadística (INE).

Table 1
Number of active FinTech firms and total revenues by market niche, 2010–2019.

Number of FinTech by niche and year	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
payment	9	14	20	25	37	39	45	52	54	60
credit	12	19	24	33	48	62	76	87	93	92
investment	19	22	29	31	34	50	59	65	70	79
insurtech	11	13	14	16	18	21	19	25	32	33
financial servs	22	26	29	35	45	50	59	68	76	80
By ownership:										
incumbent	1	2	5	8	10	11	15	16	18	20
independent	63	81	100	117	152	185	216	251	273	289
TOTAL	**64**	**83**	**105**	**125**	**162**	**196**	**231**	**267**	**291**	**309**
Total revenues by niche and year (million EUR)	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
payment	21.8	93.2	113.1	128.5	190.6	317.8	472.0	598.5	724.1	774.3
credit	28.7	29.7	45.9	66.5	84.2	125.5	197.8	273.1	377.3	501.7
investment	44.9	42.9	43.5	47.3	57.8	61.8	72.4	83.8	94.0	117.9
insurtech	53.0	48.8	56.4	62.0	72.6	78.1	77.0	82.7	131.2	124.8
financial servs	33.1	39.9	46.1	48.1	74.3	84.3	88.9	115.9	184.1	249.8
By ownership:										
incumbent	0.4	70.0	79.8	92.5	138.3	225.7	213.0	283.5	329.5	361.0
independent	146.4	157.3	188.3	216.6	282.8	373.2	628.2	787.1	1046.3	1212.2
TOTAL	**146.8**	**227.2**	**268.1**	**309.1**	**421.0**	**598.9**	**841.1**	**1070.6**	**1375.8**	**1573.3**

Source: Own elaboration. Financial data retrieved from SABI Bureau van Dijk.

shares that may result in higher levels of concentration, but the profit-structure relationship is spurious (efficiency driving both profits and market structure). However, neither SCP nor ESH explain bank profitability to a large extent (Berger, 1995), because the focus is on profits rather than the deviation of price from marginal cost, which is the correct basis for analysing competition (Paul, 1999).

Non-structural approaches, instead, are developed under the new empirical industrial organization (NEIO) approach. They provide theoretical models and assumptions on price and output determination to measure competition and assess market power based directly on firm conduct, comparing deviations between observed and marginal cost pricing without explicitly using any market structure indicator. Bikker and Bos (2005) explain that non-structural models, such as Panzar-Rosse and Bresnahan models, as well as the SCP model, may be derived from the same framework. Here, each firm i maximises profit π_i (depending on output vector Y_i, input vector X_i, output price vector p_i, and input price vector w_i) using a transformation function T and a pricing opportunity set H, capturing the firm's assessment of its competitive position.

We may then define λ_i, the **conjectural variation** of firm i's output, as $\frac{dY}{dY_i} = 1 + \frac{d\sum_{j\neq i} Y_j}{dY_i} = 1 + \lambda_i$, such that a high λ_i means that firm *i* has a high awareness of its interdependence with its rivals. Conversely, if firms are myopic (for example, they compete in Cournot or Bertrand fashion), their λ_i is zero. The result of the optimisation programme, after rearranging for λ_i, would be $\pi_i^* = p_i^* Y_i - w_i^{'} Y_i X_i^* = \left[MS_i\left(-\frac{1}{\varepsilon_D}\right)(1 + \lambda_i)\right] p_i^* Y_i$. Therefore, optimal profits π_i^* go up with an increase in market share MS_i, the conjectural variation λ_i, the price of outputs p_i^* and the demand Y_i, and a decrease in the price elasticity of demand ε_D. The different structural and non-structural models perform a partial analysis and focus on a single right-hand variable in the equation, or a combination of two variables.

Early models derived are Iwata (1974) and the SCP model, which amounts to interpreting the combined impact of λ and HHI on performance under the equation (without control variables) $\pi^* = (HHI(1 + \lambda))p^* Y$. The Bresnahan-Lau mark-up model (Bresnahan, 1982; Lau, 1982) provides a solution in terms of an equilibrium price equation that includes a mark-up not used under perfect competition, partly used under oligopoly or monopolistic competition, and fully used under monopoly (Bikker, 2003). In turn, the **Panzar-Rosse** (PR) model does not assume Cournot competition and works well with firm-specific data on gross revenues and factor prices, without needing information about equilibrium output prices and quantities for the firm and industry (Matthews et al., 2007). Assuming $\varepsilon_D > 1$ and homogeneous cost structure, firms maximise profits when marginal revenue equals marginal cost. Market power is then measured by $\frac{\partial R_i^*}{\partial w_{k_i}}$, the extent to which a change in factor input prices (∂w_{k_i}) – where *w* is a vector of K input prices – is reflected in the equilibrium revenue (∂R_i^*) earned by firm *i*. The measure of competition, the Panzar-Rosse H statistic, is then obtained as the sum of the elasticities of the reduced-form revenue with respect to the K input prices, $H = \sum_{k=1}^{K} \frac{\partial p^* Y}{\partial w_k} \frac{w_k}{p^* Y}$. The H statistic ranges between $-\infty$ and 1, with $H < 0$ denoting a monopoly, $H = 1$ indicating perfect competition, and $0 < H < 1$ being associated with forms of monopolistic competition and oligopoly.

Finally, beyond the basic framework by Bikker and Bos (2005) outlined above, two relevant indicators are the Lerner index and the

Table 2
Study variables for competition in the Spanish FinTech industry.

INDICATOR	VARIABLE	CONCEPT	DESCRIPTION	DATA SOURCE
	n	number of firms	Number of all firms in the industry at year t	hand-collected data
CR4				
	CR4	4-firm concentration ratio	Sum of MS of 4 largest firms (in %)	
	MS	market share	Ratio of annual firm revenue over total industry revenues (in %)	Annual reports 2010–2019
HHI				
	HHI	Hirschman-Herfindahl index	Sum of squared MS of all firms	
PR H statistic				
	E	E statistic	Sum of β's of the 3 input factors in estimating ROA	Regression
	ROA	Return on assets	Ratio of profit after tax to total assets (in %)	Annual reports 2010–2019
	w_1	Price of labour	Ratio of personnel expenses to number of employees	Annual reports 2010–2019
	w_2	Price of fixed capital	Ratio of operating expenses excluding personnel to total assets	Annual reports 2010–2019
	w_3	Price of financing	Ratio of interest expenses to total liabilities (in %)	Annual reports 2010–2019
	Z_1	Fixed asset ratio	Ratio of fixed assets to total assets (in %)	Annual reports 2010–2019
	Z_2	Capital ratio	Ratio of shareholders' equity to total assets (in %)	Annual reports 2010–2019
	Z_3	Provision ratio	Provision to total assets (in %)	Annual reports 2010–2019
	Z_4	Income diversification	Financial and other operating income to revenue and all income	Annual reports 2010–2019
	Z_5	Size	Logarithm of total assets	Annual reports 2010–2019
	Z_6	Ownership	Binary 0 = independent, 1 = owned by incumbent banks	SABI
	Z_7	Inflation	Consumer price index-based inflation rate	INE
	Z_8	GDP growth	Growth rate of real GDP	INE
	Z_9	HHI		
	H	H statistic	Sum of β's of the 3 input factors in estimating revenue	Regression
	R	Revenue	Total revenue	Annual reports 2010–2019
Boone				
	BI	Boone indicator	β of marginal cost in estimating profits	Regression
	π	Profits	Profit after tax	Annual reports 2010–2019
	mc	Marginal cost	Change in total cost caused by the increase in one unit of revenue	Separate regression
	c	Total cost	Sum of all operating expenses	Annual reports 2010–2019
	avc	Average variable cost	Ratio of operating expenses to revenue (in %)	Annual reports 2010–2019
Lerner				
	LI	Lerner index	Relative margin (P - mc) / P, data from conjectural variation model	Annual reports 2010–2019
Conjectural variation model				
	Q	Output	Sum of brands' online traffic in period t (proxied by Google Trends)	Annual reports 2010–2019
	P	Output price	Ratio of total revenue by the n firms to total output Q	Annual reports 2010–2019
	mc2	Variable cost per unit	Ratio of operating expenses to revenue scaled by P	Annual reports 2010–2019
	N_B	IB's market share	Sum of the FinTech owned by incumbent banks' market share	
	N_F	FF's market share	Sum of the independent FinTech firms' market share	
	H_B	IB's squared weights	See defining equation in the text	
	H_F	FF's squared weights	See defining equation in the text	
	GDP	GDP	Gross domestic product in fixed prices	INE

Boone model. The **Lerner index** (Lerner, 1934) highlights that relative margin (price minus marginal cost expressed as a percentage of price) is best for evaluating market competition, since the gap between product price and marginal cost of production is the essence of monopoly power (Fernández de Guevara et al., 2005). Thus, $LI = \frac{p-mc}{p}$, where p is the price of the good set by the firm and mc its marginal cost, ranges from 0 to 1, and the higher the value the more the firm is able to price over its marginal cost, hence the greater its market power. However, both the Lerner index and the H statistic as measures of market power face different theoretical and practical limitations (see Oduro et al., 2022). In dealing with these limitations, recent studies use the **Boone indicator** (BI) of market power (Boone, 2008), which compares the relative profit differences that result from differences in firm efficiency. Boone et al. (2005) explain this is most easily measured by $\widehat{\beta}$ from regression $\ln\pi_i = \alpha + \beta\ln mc_i + \varepsilon_i$, where π_i is the profit of each firm i, mc is marginal cost (the measure for efficiency), and β is the Boone indicator of market power – a profit elasticity that represents the percentage fall in firm's profit due to a percentage increase in its marginal cost. Since the marginal cost cannot be observed directly, Boone et al. (2005) approximate it with average variable costs (the ratio of labour costs and intermediates over revenues).

In our research, we use structural approaches (number of firms, concentration ratio and HHI index), non-structural approaches (a conjectural variation model and the H statistic), the LI and the BI. Many recent articles on the market structure of the banking industry use any of these measures. The use of the HHI index is widespread, while a non-exhaustive list of recent articles using either the H statistic or the BI includes Delis (2012), Arpegis et al. (2016), Léon (2016), Khan et al. (2017), and Capraru et al. (2020) at the international level, and specific studies on countries such as Brazil (Barbosa et al., 2015). China (Fang et al., 2019), Ghana (Oduro et al., 2022), and India (Rakshit and Bardhan, 2019). On the other hand, conjectural variation models are frequently used in the literature of strategic management (Amit et al., 1988), while specifically oriented to the analysis of the banking industry we find models by Mas-Ruiz and Ruiz-Moreno (2017) in Spain, and Zhou et al. (2021) in China. However, despite the extensive literature, we only trace one recent article specifically oriented to the analysis of market competition in the FinTech industry, in this case using the Panzar-Rosse model to analyse competition in Russia (Efimov et al., 2021). Still, Antwi-Wiafe et al. (2023) recently tested whether financial technology is a complement or substitute for traditional banks in Ghana by means of autoregressive distributive lags estimation technique.

3. Methodology and hypotheses

3.1. Indicators of market competition

In this section we analyse how market competition in the Spanish FinTech industry has evolved the last decade by means of the indicators summarised in Table 2, where the main variables and data sources used in this research are also shown.

The **four-firm concentration ratio** (CR_4) follows from simply adding the market shares (MS) of the 4 largest firms in the industry:

$$CR_4 = \sum_{i=1}^{4} MS_{it} \tag{1}$$

where $i = 1, \ldots, 4$ are the largest FinTech firms by market share in an industry of n firms, and $MS_{it} = \frac{R_{it}}{\sum_{i=1}^{n} R_{it}}$ is the market share in terms of total revenue (R_{it}) of firm i on period t.

The **Herfindahl–Hirschman index** of market concentration (HHI) is estimated by adding the squared market shares of all firms in the industry:

$$HHI = \sum_{i=1}^{n} MS_{it}^2 \tag{2}$$

Its value ranges $\frac{1}{n} \leq HHI \leq 1$, with the minimum value appearing in industries where total production is shared equally among the n firms, while $HHI = 1$ denotes a monopolistic industry with revenues concentrated in a single firm.

The **Panzar–Rosse H statistic**, defined as the sum of the elasticities of revenue with respect to a vector of K input prices, measures at which extent to which a change in input prices is reflected in the equilibrium revenue earned by firm i. The derivation of the model requires a two-step process. First, to test the long-term market equilibrium using the E statistic, defined as the sum of input price elasticities from a dynamic profit equation:

$$E = \sum_{j=1}^{3} \beta_j^{'} \tag{3}$$

where a Wald test is performed under the null hypothesis E = 0 of long-term market equilibrium. Second, the long-run H statistic is computed by estimating a reduced form of the log-normal dynamic function of the firm's revenue to finally obtain the statistic as:

$$H = \sum_{j=1}^{3} \beta_j^{''} \tag{4}$$

These estimation use the variables defined in Table 2. A complete derivation of the model is provided in the Appendix.

The **Boone indicator** (BI) is a profit elasticity representing the percentage fall in firm i's profit due to a percentage increase in its marginal cost. It is measured by $\widehat{\beta}$ in regression:

$$\ln\pi_{it} = \alpha + \beta\ln mc_{it} + \sum_{k=1}^{6}\beta_k \ln Z_{kit} + \sum_{k=7}^{9}\beta_k \ln Z_{kt} + \xi_{it} \tag{5}$$

where π_i is the profit of each firm i, mc is the marginal cost (the measure for efficiency), and Z_k is the same vector of nine control variables used in the Panzar-Rosse model. In addition, we introduced a time dummy to control for the financial and sovereign debt crises. Moreover, and since firms' marginal costs cannot be directly observed, we use two proxies: estimate the marginal cost of the FinTech firms from a trans log cost function specified in the Appendix, and we use average costs for robustness check. A complete derivation of the model is also provided in the Appendix.

Finally, the **Lerner index** (LI), defined simply as the relative margin, provides a value at firm level that is easy to interpret (a higher index value implies lower consumer welfare) and simple to estimate if information on product price and marginal costs is available:

$$LI = \frac{p - mc}{p} \tag{6}$$

Following Cruz-García et al. (2018), the empirical approach for the banking industry tends to use total assets to measure a bank's activity (since loans are the core of its business), and estimates price as the ratio of total revenues to total assets, and marginal costs with a similar trans log cost function. However, for the FinTech firms in our sample – most of them being payments service providers, crowdlending platforms and comparators – this approach does not apply. Instead, price and marginal costs will be estimated using data from the conjectural variation model below, with price estimated at the industry level and individual marginal costs proxied by the average variable cost per unit of revenue. This approximation provides an LI for each firm, while at industry level it is obtained as a weighted average of the individual indices, using revenues as weights (Cruz-García et al., 2018).

3.2. A conjectural variation model for bank-owned versus independent FinTech firms

Conjectural variation models treat firm conduct as continuous-valued parameters to be estimated in terms of firms' conjectural variations – that is, their expectations about the rivals' reactions to an increase in quantity. Gollop and Roberts (1979) allowed conjectures to vary across firms, whereas Spiller and Favaro (1984) did the same in the banking industry to emphasise on heterogeneity of firm conduct (Bresnahan, 1989).

We use a model similar to that by Zhou et al. (2021) – who follow Spiller and Favaro (1984)'s model – adapted to explain competition between two groups in the industry: the FinTech ventures by the incumbent banks (B) and the independent FinTech firms (F). Assuming that these firms produce homogenous products or services, their demand function is $P_t = P(Q_t)$, with $P'(Q_t) < 0$, where P_t is the price in period t and Q_t, $Q_t = \sum_{i=1}^{n} q_{it}$, is the total quantity produced by the n firms in the market, being q_{it} the output of firm i in period t (loans or other products and services). The first-order condition for firm i to maximise its profit is:

$$P_t + q_{it}\frac{\partial P_t}{\partial Q_t}\left[1 + \sum_{j\neq i}^{n}\frac{\partial q_{jt}}{\partial q_{it}}\right] - mc_{it} = 0 \tag{7}$$

where mc_{it} is the marginal cost. The interaction between firms is assumed to depend only on their market shares (relative sizes), as

$$\frac{\partial q_{jt}}{\partial q_{it}}\frac{q_{it}}{q_{jt}} = \beta_{it} + \gamma_{it}n_{it} \tag{8}$$

where β_{it} and γ_{it} are parameters and $n_{it} = \frac{q_{it}}{Q_t}$ is firm i's market share. Eq. (8) indicates the expected reaction of firm j, $j \neq i$, to firm i's production change, a reaction that is related to firm i's market share. Substituting Eq. (8) into Eq. (7) yields:

$$\frac{mc_{it}}{P_t} = 1 + \frac{1}{e}\left[n_{it} + \sum_{j\neq i}^{n}\left(\beta_{it}n_{it} + \gamma_{it}n_{it}n_{it}\right)\right] \tag{9}$$

where $e = \frac{\partial Q_t}{\partial P_t}\frac{P_t}{Q_t}$ is demand elasticity. The n equations for the n firms in Eq. (9) share a common variable, e, but some assumptions are needed to simplify the estimation. Thus, if homogeneous interaction were assumed, all firms would have the same reaction to the production change of a given firm, hence $\beta_{it} = \beta$ and $\gamma_{it} = \gamma$ for all i,j. Instead, we assume some group heterogeneity, in the sense that two groups of firms compete in the market, with different reaction functions within and between the two groups. The reaction functions between the two groups would be different, whereas firms in the same group face the same reaction functions; namely, $\beta_{ki} = \beta_{kj}$ and $\gamma_{ki} = \gamma_{kj};\ i,j \in B \ or \ i,j \in F$, and $\forall k, k \neq i,j$, where B and F denote the dominant group and the fringe group, respectively. This way, the $n \times (n-1)$ coefficients matrix can be simplified into eight representative coefficients, $\beta_B^B, \beta_B^F, \beta_F^B, \beta_F^F, \gamma_B^B, \gamma_B^F, \gamma_F^B, \gamma_F^F$, which are determined by reaction functions I to IV as follows:

I. $\frac{\partial q_i}{\partial q_j}\frac{q_j}{q_i} = \beta_B^B + n_j\gamma_B^B; i \in B, j \in B$

II. $\frac{\partial q_i}{\partial q_j}\frac{q_j}{q_i} = \beta_F^B + n_j\gamma_F^B; i \in F, j \in B$

III. $\frac{\partial q_i}{\partial q_j}\frac{q_j}{q_i} = \beta_F^F + n_j\gamma_F^F; i \in F, j \in F$

IV. $\frac{\partial q_i}{\partial q_j}\frac{q_j}{q_i} = \beta_B^F + n_j\gamma_B^F; i \in B, j \in F$

Reaction function I indicates the expected production change of other firms in group B when firm B_j rises production. Reaction function II indicates the expected production change of firms in group F in reaction to B_j's production increase. Reaction function III measures the expected production change of other Fs in reaction to F_j's production increase. And function IV is the expected production change of Bs in face of that change by F_j. Any of these functions being above (below) zero implies retaliation (accommodation) from rivals of firm j.

Substituting the reaction functions into the first order condition stated in Eq. (7), weighting the supply function by weights n_{it} and adding them up, we obtain:

$$\sum_{i\in B}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Bt}} = 1+\frac{1}{e}\left[\begin{array}{c} N_{Bt}H_{Bt}+\beta_B^B(N_{Bt}-N_{Bt}H_{Bt})+\gamma_B^B\left(N_{Bt}^2H_{Bt}-\sum_{i\epsilon B}\frac{n_{it}^3}{N_{Bt}}\right) \\ +\beta_F^B(1-N_{Bt})+\gamma_F^B N_{Bt}H_{Bt}(1-N_{Bt}) \end{array}\right] \tag{10}$$

as supply functions of firms in group B, and

$$\sum_{i\epsilon F}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Ft}} = 1+\frac{1}{e}\left[\begin{array}{c} N_{Ft}H_{Ft}+\beta_F^F(N_{Ft}-N_{Ft}H_{Ft})+\gamma_F^F\left(N_{Ft}^2H_{Ft}-\sum_{i\epsilon F}\frac{n_{it}^3}{N_{Ft}}\right) \\ +\beta_B^F(1-N_{Ft})+\gamma_B^F N_{Ft}H_{Ft}(1-N_{Ft}) \end{array}\right] \tag{11}$$

as supply functions of firms in group F, where $N_{Bt} = \sum_{i\in B} n_i$, $N_{Ft} = \sum_{i\in F} n_i$, $H_{Bt} = \sum_{i\in B}\frac{n_{it}^2}{N_{Bt}^2}$, and $H_{Ft} = \sum_{i\epsilon F}\frac{n_{it}^2}{N_{Ft}^2}$. We also assume that the demand function of the industry takes the constant elasticity form (see Bresnahan, 1989) given by:

$$\ln Q_t = e_0 + e\ln P_t + e_{GDP}\ln(GDP_t) + \varepsilon_t \tag{12}$$

where e denotes demand elasticity, Q_t is outstanding output in fixed prices by the n firms, and GDP is the gross domestic product in fixed prices. Eqs. (10)–(12) are the structure equations, with all of them sharing one common parameter, e. Finally, to avoid the endogeneity caused by the simultaneity bias, we use the three-stage least squares (3SLS) estimator to estimate the model.

Following Spiller and Favaro (1984), we pose the following hypotheses. First, a retaliation strategy (production increase) is expected by the dominant group – the FinTech owned by banks – when facing a production increase by another FinTech firm in the dominant group.

H1:. *Reaction function I of any* other *firm i in the dominant group B to a change in production by firm j in the same group B will show a positive reaction, as given by* $\beta_B^B + n_i\gamma_B^B > 0, i \in B$.

In contrast, an independent FinTech firm would reduce production in response to a production increase by a firm owned by the incumbent banks (accommodative strategy).

H2:. *Reaction function II of any* firm *i in the fringe group F to a change in production by a firm j in the dominant group B will show a negative reaction, as given by* $\beta_F^B + n_i\gamma_F^B < 0, i \in B$.

Third, no interaction is expected among firms in the fringe group (the independent FinTech start-ups).

H3. Reaction function III of any other firm i in the fringe group F to a change in production by firm j in the same group F will show no reaction, as given by $\beta_F^F + n_i\gamma_F^F \approx 0, i \in F$.

Finally, a small production increase is expected from FinTech firms in the dominant group in response to a production increase by an independent firm (little retaliation).

H4:. *Reaction function IV of* any *firm i in the dominant group B to a change in production by a firm j in the fringe group F will show little retaliation, as given by* $\beta_B^F + n_i\gamma_B^F \geq 0, i \in F$.

In this framework, FinTech firms in the dominant group would have a certain level of monopolistic power and are expected to be hardly influenced by the behaviour of the independent FinTech firms.

4. Degree of market competition in the Spanish FinTech industry

4.1. Sample

To assemble a comprehensive overview of the Spanish FinTech industry, we used a broad Internet search encompassing four steps. We started by retrieving a list of brands listed as FinTech firms in the main Spanish FinTech associations or identified as such in the existing FinTech "radars".[11] Second, we enlarged the list with the directories of the respective national supervisory authorities,[12] and the census and sources recently provided by Banco de España (Sánchez and Quintanero, 2022). The third step consisted of screening and filtering out of potentially misclassified firms, through an individual analysis of their websites, the business description there provided, contact information and other corporate information. This allowed to filter out a large list of companies that actually operate online from abroad, 44 brands for which we could not obtain any information about services provided or the company itself, and 45 firms that do not meet the definition by the Financial Stability Board of the Bank for International Settlements.[13] In case of doubt, we opted to classify them in the category of "other financial services". Finally, in a fourth step, we regularly updated the list from March 2021 to September 2022 with using news articles about FinTech in mainstream press and specialised sites,[14] and the information provided by some of the incumbent banks (mainly, Abanca Innova, Bankinter, and BBVA).

Our sample consists of a subset of this dataset: the 202 firms that operate in the segments of payment services (83) and credit (123) (some firms were classified in both categories).[15] Their financial statements from 2010–2019 were retrieved from SABI Bureau van Dijk database. It deserves mention that the financial reporting standards by financial institutions are different than those by ordinary firms – in Spain, in accordance with regulation issued by the BdE.[16] However, all the FinTech firms in the sample are classified as ordinary firms. This implies that the measurement of indicators that make use of information provided by financial institutions – e.g., loans and deposits in the balance sheet and interest income and net interest income in the income statement – will require reformulation.

Fig. 2 shows the boost of interest in payment services and credit FinTech firms, with seven times more companies operating at the end of the period than early in the decade, and total revenues multiplying about 20 times – up to 1.35 billion euros in 2019. Strong revenue growth is observed from 2015 onwards.

Next, we use the indicators of market competition described in Section 3. Fig. 3 shows the evolution of CR_4 and the HHI of the industry during the period of analysis.

Both indicators point out to a decreasing concentration in the context of the emergence of new competitors in the industry. Thus, the four largest firms had more than 80% of the market share in years 2010–2012, only to decrease to CR_4 ratios in the range of 55–60% from 2014 to 2017 and falling to 50% afterwards. The largest firm accounted for 57.1% of the revenues in 2011, decreasing to 28.4% in 2014 and falling below 21.0% in 2019. This is similar to the information provided by the HHI index, with a steep drop from 2011 to 2014, when the index fell from 0.36 to 0.13. The trend moderated thereafter but has continued to decrease steadily to a value of 0.09 in 2019. All these values are representative of an atomised industry.

4.2. Results by indicator

In this section we measure the H statistic, the BI, and the LI. Table 3 provides descriptive statistics for the variables used. Data is winsorised at the 1% and 99% for all continuous regressors, with 873 year-firm observations available (after any observations with zero revenues were discarded).

For the **PR model**, we first test the E statistic for long-term market equilibrium. The results of the 2-step GMM are provided in Table 4: the E statistic, the sum of the $\beta_j^{'}$ coefficients in the regression, amounts to $E = -0.067$, and the Wald test shows it is different from zero ($chi^2(1)$ 6.93, p=0.008), implying long-term market disequilibrium. Hence, a dynamic specification to estimate the H statistic is required to accommodate the persistence of the dependent variable in the determination of market competition.

[11] Most firms were obtained at: AEFI – Asociación Española de Fintech e Insurtech (www.asociacionfintech.es), Finnovista radar (www.finnovista.com), and EFA – European Fintech Association (www.eufintechs.com/). Other directories include Universo Fintech, ACLE – Asociación de Crowlending Española,

[12] These include Comisión Nacional del Mercado de Valores (CNMV) for registries on dealer and brokerage services, crowdfunding and crowdlending firms (plataformas de financiación participativa, PFP), Banco de España (BdE) for registries on credit financial institutions (entidades financieras de crédito, EFC), electronic money institutions (entidades de dinero electrónico, EDE), and payment institutions (entidades de pago), and Dirección General de Seguros (DGS) on insurance companies. Furthermore, since 2020 the CNMV has regularly issued a series of warnings on entities that are providing financial services without authorisation. We double checked these warnings of more than 2000 companies (most of them foreigners), to identify additional FinTech firms. While mapping the whole universe of FinTech – and particularly, of crypto exchanges – is impossible, it ensures us that any Spanish crypto operator identified by the Spanish regulator has been included in the list.

[13] Fintech firms are here defined as technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services. According to these, we have excluded from our database any comparators and platforms related to real estate investments, arts, and similar.

[14] Such as cointelegraph.com, finanzas.com, finnovating.com and spainfinancialcentre.com, among others.

[15] The list of firms is provided in the Appendix.

[16] *Circular 4/2017 del Banco de España*. Available at https://www.bde.es/bde/es/secciones/normativas/ Regulacion_de_En/Estatal/Contabilidad.html

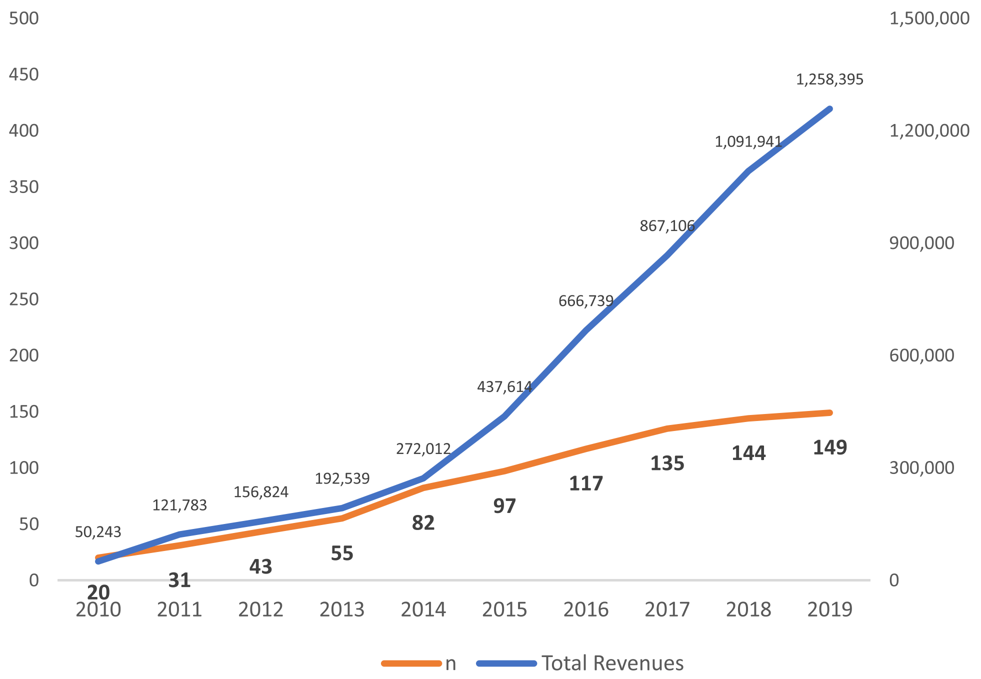

Fig. 2. Number of firms and total revenues in the Spanish FinTech industry, 2010–2019.

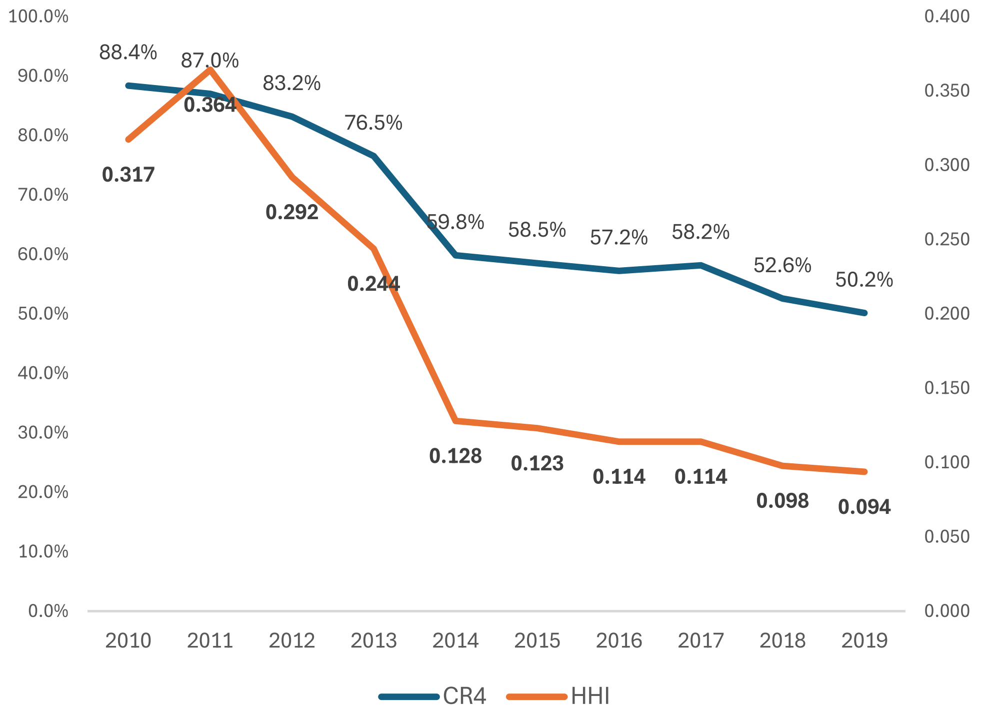

Fig. 3. Concentration ratio and HHI index in the Spanish FinTech industry, 2010–2019.

Table 3
Descriptive statistics, 2010–2019.

Variable	N	Mean	std.dev.	min	p25	median	p75	max
n	873	111.36	38.27	20.00	82.00	117.00	144.00	149.00
MS	873	0.01	0.05	0.00	0.00	0.00	0.00	0.57
ROA	857	-21.95	47.41	-281.10	-33.80	-7.10	2.60	55.70
w1	719	36.40	18.56	1.76	23.97	33.22	45.73	118.68
w2	860	0.82	1.09	0.03	0.25	0.51	0.98	10.85
w3	862	1.72	3.22	0.00	0.00	0.50	2.10	33.50
Z1	865	35.78	29.86	0.00	6.90	30.90	62,70	98.00
Z2	866	25.08	50.46	-100.00	2.40	30.50	64,10	99.10
Z3	861	0.25	2.81	-0.20	0.00	0.00	0.00	42.70
Z4	865	15.08	20.49	-1.09	0.00	1.39	35.28	50.00
Z5	857	6.61	2.00	1.84	5.37	6.48	7.69	12.83
Z6	873	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Z7	873	0.94	0.96	-1.00	0.30	1.10	1.20	3.00
Z8	873	1.84	1.81	-3.36	1.60	2.22	3.12	4.09
Z9	873	0.14	0.07	0.09	0.10	0.11	0.13	0.36
R	857	4193.4	12,638.5	0.16	67.13	331.10	1497.5	86,801.0
profit	856	31.01	1809.5	-6257.1	-198.36	-22.09	19.45	17,122.0
cost	857	3977.4	10,934.7	4.34	149.96	511.46	1784.5	76,401.6
avc	857	7.81	36.53	0.23	0.95	1.15	2.52	574,07
price	873	0.22	0.06	0.17	0.20	0.20	0.22	0.43

Table 4
Panzar-Rosse model: E statistic and H statistic. Two-step system GMM, 2010–2019.

Dependent	**lnROA**			Dependent	**lnR**		
Coefficients	Coef.	Std. Err.	z	**Coefficients**	Coef.	Std. Err.	z
lnROAlag1	-0.0012	0.0527	-0.02	lnRlag1	0.0326	0.0344	0.95
w1	-0.0023	0.0022	-1.04	w1	-0.0062	0.0060	-1.03
w2	-0.0362	0.0245	-1.48	w2	0.5463	0.1189	4.59***
w3	-0.0286	0.0089	-3.21***	w3	0.0305	0.0207	1.48
Z1	-0.0076	0.0018	-4.19***	Z1	0.0076	0.0039	1.97**
Z2	0.0056	0.0013	4.25***	Z2	0.0021	0.0021	1.01
Z3	0.0044	0.0037	1.19	Z3	0.0001	0.0080	0.01
Z4	0.0026	0.0024	1.07	Z4	0.0056	0.0044	1.29
Z5	0.0744	0.0554	1.34	Z5	1.3700	0.0911	15.04***
Z6	-1.0728	0.8468	-1.27	Z6	2.0848	3.0358	0.69
Z7	-0.0171	0.0188	-0.91	Z8	-0.0170	0.0487	-0.35
Z8	-0.0352	0.0197	-1.79*	Z9	-0.5568	2.1478	-0.26
Z9	-0.7259	0.6818	-1.06	year fixed effects			
constant	-0.27	0.55	-0.48	constant	-4.11	0.95	-4.33***
Model statistics				**Model statistics**			
N. observ.	575	Wald chi^2	120.7***	N. observ.	654	Wald chi^2	7440.5***
N. groups	149	AR(2)	-0.33	N. groups	158	AR(2)	0.55
N. instrum.	26	Sargan chi^2	35.0***	N. instrum.	38	Sargan chi^2	97.7***
		Hansen chi^2	17.2			Hansen chi^2	15.8
Long-run market equilibrium test				**Test for competitiveness**			
E statistic	-0.0672			H statistic	0.5707	(Monopolistic competition)	
H_0: E = 0	6.93	chi^2 (1) p-val	0.008 (Disequil.)	H_0: H = 0	22.10	chi^2 (1) p-val	0.000 (no monopoly)

Notes: GMM with collapsed instruments.
* significant al 10%
** significant at 5%
*** significant at 1%.

Arellano–Bond tests of the assumption of serially uncorrelated errors yield p<0.05 for first-order autocorrelation (AR1) and p>0.1 for second-order autocorrelation (AR2), as expected.[17]

The H statistic is then estimated. Measured as the sum of the β_j'' regression coefficients, its value is $\boldsymbol{H = 0.57}$ with collapsed instruments and year fixed effects.[18] Being in the range of $0 < H < 1$, it suggests some form of monopolistic competition in the industry. Again, Arellano–Bond tests yield p=0.07 for AR1 and p>0.1 for AR2, as expected.

[17] Following Roodman (2009), we collapsed instruments to limit instrument proliferation and improve the power of the Hansen test. The rule of thumb of groups (149) largely outnumbering instruments (26) is satisfied.
[18] Again, the number of groups (158) largely outnumbers instruments (38) after collapsing.

Next, we estimate **BI**. First, we compute the marginal costs of each bank and year by estimating the trans log cost function stated in Eq. (A6) and then substituting the parameter estimates in Eq. (A7) to get the marginal cost. Then, the indicator is estimated with a GMM regression, with 1-year, 2-year and 3-year lagged marginal costs as instrumental variables. A dummy variable was used to control for crisis years of 2010–2013. The results are provided in Table 5. The value of the indicator is $\boldsymbol{BI = -1.61}$ among firms with positive profits, but $\boldsymbol{BI = -0.42}$ if all firms are considered (profits normalised to positive numbers).[19] Following Delis (2012), higher (less negative) values of the BI indicator indicate higher levels of market power, with average values usually ranging between −2.0 and −4.0 in high income countries. Hence, our results suggest a low degree of market competition among profitable companies, and very high market power of these firms relative to those in the Spanish FinTech industry experiencing losses. Still, only the result for all firms is robust to using average costs as a proxy for the marginal cost, with competition among profitable firms being much fiercer (higher than 4.0) when average costs are used.

Consequently, we use the **LI** to complement the interpretation. Since this index can be estimated at individual level, it helps to understand why we might be seeing vague results: for many FinTech firms in Spain, being profitable is, for the time being, a pipe dream. The histogram on the left-hand side of Fig. 4 shows that a large proportion of firms exhibit negative relative margins. These in many cases are startups with large investments and operating expenses after launching, but very low revenues. Still, the large negative values observed might be a result of how marginal costs were proxied (as the ratio of operating expenses to revenue scaled by the price). When only firms with positive profits are considered, near 90% of them show Lerner indices between 0 and 0.4 (histogram on the right-hand side of Fig. 4). In this case, the LI at industry level during the decade, obtained as a weighted average of the individual indices using revenues as weights, amounts to $\boldsymbol{LI = 17.0}$% (8.0% if year-firms with negative profits are also included). This compares relatively low to the LI for banks in Spain, usually in the range of 30–40% (Cruz-García et al., 2018), suggesting a lower market power of FinTech firms.

An analysis of the evolution of market power may provide some additional insight. Fig. 5 shows the performance over time of H statistic and BI (LHS) and LI (RHS, for all firms and firms with positive profits compared). This is intended mostly for descriptive purposes, since H and BI had to be estimated with robust OLS regressions for groups of three years (due to the reduced number of observations per year).

The LI is quite stable in the range of 10–30%, with a nuance. Thus, it shows that many firms struggled to achieve positive returns during the crisis, while competition after 2015 largely reduced their profitability. The BI provides a similar intuition, with a trend of increasing competition over time. The low levels of competition we obtained above for the complete sample may be driven by the impact of the crisis, when the indicator values might not be quite representative (there were few firms, most of them running losses). More recently, the value is near −2.5, implying moderate competition. The H statistic suggests monopolistic competition as well (often ranging 0.4–0.6), but the peak of competition is instead observed by 2015 (when a strong revenue growth was observed in the industry, according to Fig. 2). The trend shown by the BI and the LI would be consistent with trend by the structural measures (CR_4 and HHI), while the peak by the H statistic coincides with the sharpest decrease of the structural measures in 2014.

5. Strategic interaction in the Spanish FinTech industry

Once we characterised overall market competition among FinTech firms of any kind, now we use the conjectural variation approach described in Section 3 to answer the question of whether bank-owned FinTech ventures and independent FinTech start-ups compete or collaborate. We identify as FinTech firms owned by banks (B) any FinTech firm owned by or allied to incumbent banks (treatment group = '*incumbent*'), and the rest as independent FinTech firms (F). For robustness, we also test the model using as treatment group only FinTech firms exclusively owned by incumbent banks (treatment group = '*owned*').

Following Zhou et al. (2021), total industry output (Q) would be the sum of any financial products offered by the banking sector to customers. Usually proxied as total loans in the industry,[20] for FinTech firms we must accommodate this measure to their reality. Thus, a proxy is needed that accounts for the services provided by a heterogeneous mix of payments services providers, crowdlending platforms, comparators, etc. Here we use the sum of the online traffic every year by all the FinTech brands. As proxy, we use Google Trends as measure of the popularity of the brands in Google Search in Spain every year, to obtain an annual estimate for the industry output. The output price (P) of the FinTech industry is hence estimated annually as the ratio of the sum of total revenue by the $\boldsymbol{n}$ firms to total output Q, interpreted as the average price for the services provided at the industry level. An individual estimate of the marginal cost is proxied by the average variable cost per unit of revenue (mc2), measured as the ratio of operating expenses to total revenue scaled by P.

Considering *incumbent* as treatment group, we regress the simultaneous equations model provided by Eqs. (10)–(12) with the 3SLS estimator. Since Eqs. (10) and (11) are added up at the cross-sectional level, despite having 202 firms the resulting regressions are under identified for 10 annual observations and 12 parameters overall. To overcome this, we have interpolated data between each pair of annual observations. Table 6 shows that the resulting regression coefficients are almost identical to those obtained by regressing the identical cross-sectional data for all firms in the database (coefficients that would be more precise for the real data available but unsuitable for hypothesis testing).

[19] Hansen J-test required introducing one of the lagged variables in the model for it to be correctly specified.

[20] In a model à la Zhou et al. (2021) of banks providing loans only, the output price would be estimated as interest income to total loans. Here, FinTech firms operate in different segments other than credit supply and, what is more relevant, information in the annual reports is provided in the regular format, without specifying loans, deposits or interest income. Hence, we an alternative measure will need to be specified.

Table 5
Boone indicator. Two-step system GMM, 2010–2019.

Dependent	**ln profit**		
Coefficients	Coef.	Robust Std. Err.	z
ln mc	-1.6070	0.6162	-2.61***
ln mc lag3	1.5902	0.3161	5.03***
Z1	-0.0081	0.0052	-1.54
Z2	0.0155	0.0064	2.44**
Z3	0.0523	0.0127	4.13***
Z4	-0.0046	0.0141	-0.33
Z5	0.5821	0.1657	3.51***
Z6	1.3597	0.7878	1.73*
Z7	0.2352	0.2237	1.05
Z8	0.5361	0.1922	2.79***
Z9	-9.9783	6.7996	-1.47
crisis	1.9889	1.4883	1.34
constant	-7.70	1.87	-4.11***
Model statistics			
N. observ.	77		
Hansen's J-test chi^2	0.858	J-test sig	0.354

Note:
* significant al 10%
** significant at 5%;
*** significant at 1%.

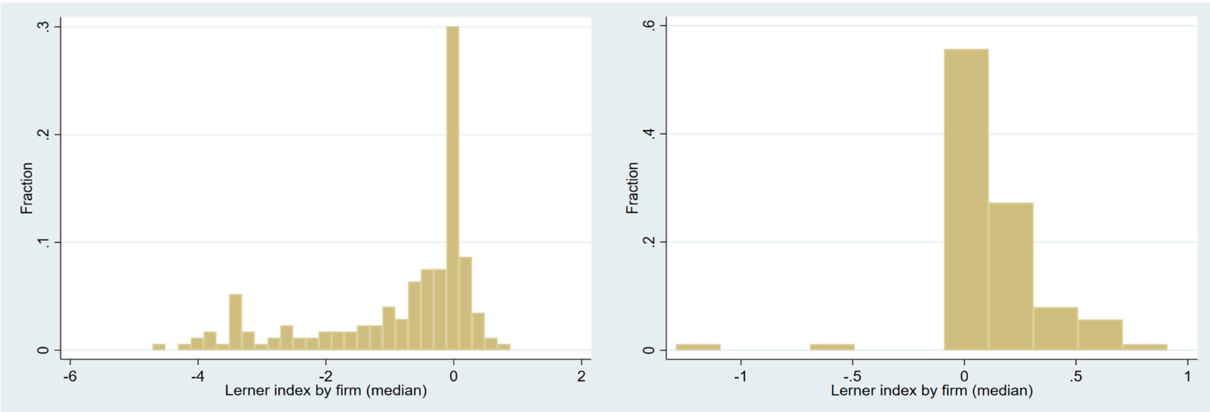

Fig. 4. Histogram of individual Lerner indices, median values for 2010–2019.

Table 6 shows a demand elasticity of −2.4 (a negative relationship between demand and price consistent with our expectations) and that most coefficients in the three equations are tested significant. However, they are not the relevant ones to interpret; we need to test the four reaction functions to investigate the interactions between the FinTech owned by banks and the independent firms. To obtain the reaction functions I to IV we proceed as follows:

- We solve for βs and γs in reaction functions I and II using Eq. (10) results solving for elasticity e estimated in Eq. (12). Then, we estimate the reaction functions for a given market share n_j. The results are provided in Table 7 for market shares of 90th, 75th, 50th, 25th and 10th percentiles from each group of firms that are forming conjectures.
- We do the same for βs and γs in reaction functions III and IV using Eq. (11) solving for the elasticity e estimated in Eq. (12), and then estimate the reaction functions for different market shares n_j.

The results, provided in Table 7, are identical whether we include as treatment firms those that are either owned by or allied to banks or only those that are owned. Moreover, most results are consistent for different market shares of both groups of firms. We find that, first, all firms adopt a retaliation strategy when coping with a production increase by a rival in the same group, whether this is a FinTech owned by an incumbent bank (hypothesis H1) or an independent one (hypothesis H4). The effect is stronger the larger the market share of peer competitors. Second, the independent FinTech firms show accommodation in response to a production increase by a FinTech owned by a bank (hypothesis H2). However, and contrary to hypothesis H3, the group of FinTech firms owned by banks do exhibit some degree of retaliation if an independent firm increases production – suggesting competition rather than collaboration by the incumbent banks.

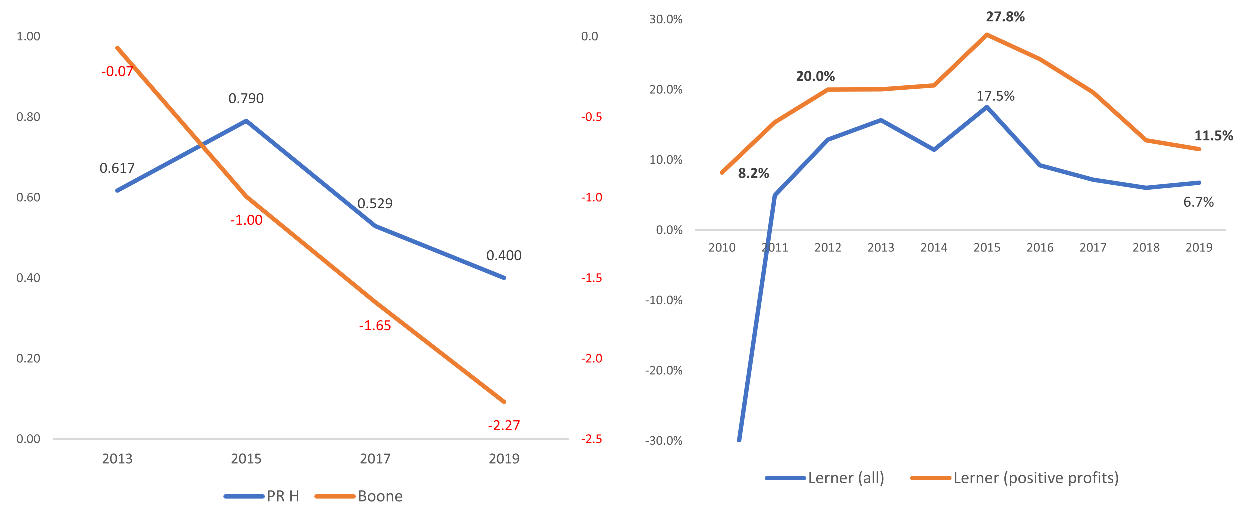

Fig. 5. Market power over time, 2010–2019.

Table 6
Conjectural variation model: parametric estimation, 2010–2019.

Treatment group: Incumbent								
Equation 1: bank-owned FinTech			**Equation 2: independent FinTech**			**Equation 3: demand function**		
Coefficient	**Estimate**	**Std. Err.**	**Coefficient**	**Estimate**	**Std. Err.**	**Coefficient**	**Estimate**	**Std. Err.**
β_B^B/e	4.5	0.4762***	β_F^F/e	0.8	0.8722	e	-2.4	0.2560***
γ_B^B/e	-19.2	2.6265	γ_F^F/e	-38.1	22.426*	e_0	-43.8	7.3536***
β_F^B/e	0.0	0.0000***	β_B^F/e	0.0	0.0000	e_{GDP}	10.4	1.6252***
γ_F^B/e	5.4	1.0423***	γ_B^F/e	-18.6	9.1576**			
Treatment group: Owned FinTech								
Equation 1: bank-owned FinTech			**Equation 2: independent FinTech**			**Equation 3: demand function**		
Coefficient	**Estimate**	**Std. Err.**	**Coefficient**	**Estimate**	**Std. Err.**	**Coefficient**	**Estimate**	**Std. Err.**
β_B^B/e	5.8	0.9828***	β_F^F/e	0.3	0.4933	e	-2.4	0.2604***
γ_B^B/e	-41.8	6.1238***	γ_F^F/e	-14.1	7.2310**	e_0	-40.9	7.4594***
β_F^B/e	0.0	0.0000	β_B^F/e	0.0	0.0000	e_{GDP}	9.8	1.6496***
γ_F^B/e	8.5	1.0850***	γ_B^F/e	-5.7	2.3234**			

Note:
Eq. (1) and Eq. (2) include $\sum_{i\in B}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Bt}}$ and $\sum_{i\in F}\frac{mc_{it}}{P_t}\frac{n_{it}}{N_{Ft}}$ as dependent variables, respectively.
Standard errors presented in the table are robust.
B, the FinTech interests of incumbent banks. F, the independent FinTech firms.
* significant al 10%
** significant at 5%
*** significant at 1%.

6. Discussion of results

The analysis of the more than 200 FinTech firms that operated in Spain during the decade of 2010 s in the segments of payment services and credit shows a strong growth in the industry, with the number of firms growing sevenfold and revenues twentyfold – even faster than the tenfold increase in revenue observed worldwide from 2013 to 2021 (KPMG, 2022).

The set of indicators of concentration and market competition used show a sharp reduction in the degree of market concentration after 2014, with CR4 and HHI showing this is an atomised industry. Still, only moderate, albeit increasing, competition levels are observed. Thus, the Panzar-Rosse model defines the industry as monopolistic competition. Moreover, the Lerner index suggests that FinTech firms have less market power than the levels often observed for banks in Spain (Cruz-García et al., 2018), although the Boone indicator suggests that profitable FinTech firms are able to exert high market power relative to their loss-making competitors. Notably, numerous FinTech startups have found it difficult to achieve profitability: they faced large initial investments and operating expenses after the launch, but had very low revenues in return, making operating margins negative in most cases. Competition after 2015 exacerbated this profitability problem for most of them.

These findings remained consistent when subjected to a series of robustness tests. These include (i) collapsing instruments in the PR model to limit instrument proliferation and improve the power of the Hansen tests; an estimation of the LI for both all sample and for only firms with positive profits; and (iii), for the BI, the use of average costs rather than the marginal costs of the FinTech firms through

Table 7
Hypothesis testing of the reaction functions, 2010–2019.

Treatment group: Incumbent						
Reaction fn.						
I	-1.1***	0.1	2.2***	4.2***	5.4***	**Favour H1 (>0)**
	0.00	0.14	0.00	0.00	0.00	
II	-0.2***	-0.6***	-1.1***	-1.7***	-2.0***	**Favour H2 (<0)**
	0.00	0.00	0.00	0.00	0.00	
III	14.1**	11.7*	7.7*	3.7*	1.3*	**Against H3 (≈0)**
	0.04	0.08	0.09	0.09	0.10	
IV	7.0*	5.9*	3.9*	2.0*	0.8*	**Favour H4 (>0)**
	0.05	0.05	0.05	0.05	0.05	
market share n_j (B)	**10%**	**25%**	**50%**	**75%**	**90%**	
market share n_j (F)	90%	75%	50%	25%	10%	
Treatment group: Owned FinTech						
Reaction fn.						
I	-0.7***	1.9***	6.3***	10.6***	13.2***	**Favour H1 (>0)**
	0.00	0.00	0.00	0.00	0.00	
II	-0.4***	-0.9***	-1.8***	-2.7***	-3.2***	**Favour H2 (<0)**
	0.00	0.00	0.00	0.00	0.00	
III	5.2***	4.3**	2.8**	1.3**	0.5**	**Against H3 (≈0)**
	0.00	0.02	0.04	0.04	0.05	
IV	2.1**	1.8**	1.2**	0.6**	0.2	**Favour H4 (>0)**
	0.02	0.01	0.01	0.01	0.01**	
market share n_j (B)	**10%**	**25%**	**50%**	**75%**	**90%**	
market share n_j (F)	90%	75%	50%	25%	10%	

Note:
p-values are tests of Prob > chi2 for the null hypothesis of the reaction functions being equal to zero for that specific sum of market shares n_j(B) and n_j(F).
B, the FinTech interests of incumbent banks. F, the independent FinTech firms. Market shares indicate that we selected those percentile FinTech firms, respectively, from the group of Bs or Fs, to form the conjecture.
* significant al 10%
** significant at 5%
*** significant at 1%.

a trans log cost function. In this latter case, competition among profitable FinTech firms appeared to be fiercer if average costs were used. Finally, we also analysed the evolution of market power over time of H statistic, Boone indicator, and Lerner index.

Our results add a notable contribution to the scarce literature on the subject. Thus, regarding concentration levels in the industry, only Polasik et al. (2020) highlighting the boost in licensed payment institutions in the European Union, with a fivefold increase after 2017, and Kliber et al. (2021) discussing several obstacles to the further development of the industry, including the lack of regulation, can be listed. Second, regarding competition levels, very little research can also be traced. To the best of our knowledge, only Efimov et al. (2021) test competition by means of any of the indicators of market competition we use here – namely, the Panzar-Rosse model. They show that monopolistic competition exists in the Russian FinTech market, similar to the results we find for Spain. Related research includes Romanova and Kudinska (2016), who find increasing competition in the FinTech industry of the US and several European countries, and Jun and Yeo (2016), who suggest that proper regulation is needed to avoid vertically integrated incumbent banks from not providing back-end services to the FinTech firms entering the retail payments market.

Third, we neither find research specifically designed to test the profitability of FinTech startups, with most studies focusing on the impact on banks' profitability of using new financial technologies. Extant research (Chhaidar et al., 2023; Mirza et al., 2023) finds mostly positive results mediated by bank size, human capital efficiency, and market concentration, among others. Wang et al. (2021a) show that the positive impact on profitability and competitiveness comes from banks' reduced operating costs, improved service efficiency, enhanced customer-oriented business models, and better risk control capabilities. Only Zhao et al. (2022b) find negative results for Chinese banks, with FinTech innovation reducing banks' profitability and asset quality, mostly by large state-owned commercial banks.

The second part of our research uses a conjectural variation model to explore whether the incumbent banks use their ventures to compete or collaborate with the independent firms, providing a clear-cut result. Independent FinTech start-ups tend to show accommodation when a bank-owned FinTech increases its production level, whereas FinTech ventures owned by banks do exhibit retaliation to production increases by independent start-ups. This suggests that the incumbent banks behave competitively rather than collaboratively. Hence the moderate levels of competition overall suggested by market competition indicators are coupled with the fact that incumbent banks as the most aggressive players in the Fintech industry. For robustness, we considered not just bank-owned FinTech firms but also allied firms, with all findings remaining consistent.

This behaviour has never been reported before. To the best of our knowledge, this is the first study to apply a conjectural variation model to the FinTech industry. Even more, while the academic literature extensively adopts both structural and non-structural approaches to measure banking competition, the absence of research on market competition in the FinTech industry (with the aforementioned exception of Efimov et al., 2021) and the fact that our methodology also allows to assess whether firms compete or collaborate make this study an interesting starting point to analyse this and other similar industries.

Still, we may relate our results to those obtained by extant research analysing collaboration between banks and FinTech start-ups by means of different methodologies. Most research are theoretical models, including those that study cooperation between incumbent banks and FinTech start-ups (Bömer and Hannes, 2018; Bartolacci et al., 2022; Ruhland and Wiese, 2023). Gozman et al. (2018) list different mechanisms of competition and cooperation among FinTech startups, such as disintermediation, access extension, personalisation, financialization, and hybridisation. On the empirical side, most results are in line with our results suggesting competition, rather than collaboration, by banks. Thus, Antwi-Wiafe et al. (2023) find significant negative impact on Ghanaian banks' performance, indicating that FinTech serves as substitutes rather than complements. In turn, Gao and Wang (2023) observe that digital finance has a significant positive effect on bank competition by means of the coverage breadth of digital finance, confirming the "catfish effect of digital finance", by which a strong competitor causes the weak to better themselves. Wang et al. (2021b) also show how FinTech development in China exacerbated banks' risk taking. Finally, we highlight two articles with interesting interpretations in terms of policy making. Exploring the relationship between FinTech and commercial bank risk-taking, Zhao et al. (2023) find that macroprudential policies weaken the effect of capital raising technology on bank risk-taking. Besides, Zhao et al. (2022a) observe increasing regional heterogeneity of fintech inclusion, with differences mainly due to supply, demand, and societal characteristics.

7. Conclusions

We delved into the reaction of traditional banks to the emergence of a new competitor on a global scale – the financial technology firms. Using the Spanish FinTech industry as a case study, we address the question: do FinTech firms and incumbent banks compete or collaborate? To this end, we used two complementary approaches: on one hand, a number of concentration measures and indicators of market competition to evaluate how market structure has evolved in this industry; on the other hand, an oligopolistic conjectural variation model we built to test whether incumbent banks use their FinTech ventures to compete or collaborate with independent FinTech rivals.

The analysis of market competition among payment services providers and credit FinTech shows that the decade of 2010 s was a period of strong growth, with seven times more firms at the end of the period than early in the decade, and total revenues increasing more than twentyfold. Both the HHI index and concentration ratios show sharp reductions in market concentration, particularly from 2011 to 2014, resulting in a highly atomised industry. Still, the measures of market power (Panzar-Rosse H statistic, Boone indicator and Lerner index) suggest only moderate levels of competition – though often increasing recently.

A complementary interpretation is provided by an oligopolistic conjectural variation model that allows to test competition between banks (through the FinTech ventures owned by or allied to them) and the independent FinTech start-ups. Our model shows that strategic interactions between and within the two groups of FinTech firms do exist, with a clear pattern of competition rather than collaboration by the incumbent banks. Put differently, our findings suggest that traditional banks are using their FinTech ventures to compete against the new players in the industry, seeking to preserve their competitive leadership.

Despite the widespread use in the academic literature of structural and non-structural approaches to characterise competition in banking industries, it is noteworthy that a single article specifically oriented to the analysis of market competition in the Russian FinTech industry (Efimov et al., 2021) can be traced, and another one oriented to test FinTech as complement or substitute for traditional banks in the Ghanaian market (Antwi-Wiafe et al., 2023). Still, we may relate our results to those obtained by Wang et al. (2021b), who have recently shown how the development of FinTech has exacerbated banks' risk taking in China. Perhaps this is due to the novelty of the topic and lack of sufficient data, so future research should help characterise the reaction of banks to the irruption of FinTech firms.

Our results can lead authorities to draw lessons for policy-making in terms of a regulation that favours independent start-ups so that they can compete on a level playing field. This would be in line with recent advances in areas such as the impact of the revised Payment Services Directive (PSD2) regulation in Europe or the implementation of regulatory sandboxes for the FinTech industry in countries such as Canada, Spain, UK or The Netherlands. Ensuring a competitive fintech industry may also contribute to the use of financial technology in rural areas (Hasan et al., 2023) and regional homogeneity of FinTech inclusion (Zhao et al., 2022).

Our study still shows some limitations, such as those imposed by lack of quarterly financial data for private companies in Spain, and the need to proxy total output of the industry through an estimate of their annual online traffic. Future research might try to overcome these limitations, as well as linking patterns of market competition to key drivers of FinTech success (see Hua and Huang, 2021) and identifying which actors are doing more for financial inclusion (see Demir et al., 2022). Moreover, being the FinTech sector intensive in technology and human capital, future research might explore the use of a different production function to obtain the measures of competition, one in which ICT capital and human capital are used as factors instead of capital measured as fixed assets to total assets. Beyond that, the well-known limits of using concentration as a measure of competition should also be considered.

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CRediT authorship contribution statement

David Peón: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft. **Yanfei Sun:** Data curation, Formal analysis, Funding acquisition, Methodology, Software, Validation, Writing – review & editing. **Manel Antelo:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare no conflicts of interest.

Data availability

Data will be made available on request.

Methodological Appendix

Indicators of market competition

Panzar–Rosse H statistic. Defined as the sum of the elasticities of revenue with respect to a vector of K input prices:

$$H = \sum_{k=1}^{K} \frac{\partial p^* Y}{\partial w_k} \frac{w_k}{p^* Y} \tag{A1}$$

Market power is thus measured by the extent to which a change in factor input prices is reflected in the equilibrium revenue earned by firm i, ranging from monopoly ($H < 0$) to perfect competition $H = 1$. Bikker and Bos (2005) argue that if the Panzar-Rosse model is to yield plausible results, firms need to have operated in long-term equilibrium (that is, the number of firms needs to be endogenous to the model). Consequently, we first test the long-term market equilibrium using the E statistic, defined as the sum of input price elasticities from a dynamic profit equation specified as follows (Kumar and Gulati, 2018):

$$\ln(1 + ROA_{it}) = \alpha' + \lambda' \ln(1 + ROA_{it-1}) + \sum_{j=1}^{3} \beta_j' \ln w_{j_{it}} + \sum_{k=1}^{6} \gamma_k' \ln Z_{k_{it}} + \sum_{k=7}^{9} \gamma_k' \ln Z_{k_t} + \varepsilon_{it} \tag{A2}$$

where return on assets (ROA_{it}) is measured as profit after tax to total assets, w_j denotes the price of three inputs (labour, fixed asset, and financing), and Z_k is a vector of nine control variables, six of them for individual risks and costs (fixed asset ratio, capital ratio, provision ratio, an income diversification measure inspired by Laeven and Levine, 2007, as well as size and ownership following Oduro et al. (2022), in order to have the same control variables as in the Boone indicator) plus other three industry and macroeconomic control variables (HHI, inflation and GDP growth).

The E statistic is then defined as

$$E = \sum_{j=1}^{3} \beta_j' \tag{A3}$$

A Wald test is performed under the null hypothesis E = 0 of long-term market equilibrium. Otherwise, using a dynamic specification of the PR model is needed, since it accommodates the persistence of the dependent variable in competition determination. Then, the long-run H statistic is computed by estimating a reduced form of the log-normal dynamic function of the firm's revenue, specified as follows:

$$\ln R_{it} = \alpha'' + \lambda'' \ln R_{it-1} + \sum_{j=1}^{3} \beta_j'' \ln w_{jt} + \sum_{k=1}^{6} \gamma_k'' \ln Z_{k_{it}} + \sum_{k=7}^{9} \gamma_k'' \ln Z_{k_t} + u_{it} \tag{A4}$$

where R_{it} is total revenue of the ith firm on period t, λ'' is the persistence coefficient, and the other variables are as explained above. Year fixed effects are added to control for the potential disruption effects of the financial and sovereign debt crises in Spain during the decade. To overcome endogeneity issues, a similar estimation strategy to that by Goddard and Wilson (2009) is employed, but using a two-step system GMM (generalised method of moments) approach with the lag of the explanatory variables as instruments rather than a first-difference GMM approach, as it provides more efficient estimators and reduces the potential biases of short time panels and in case of strong persistence in the lagged revenue variable (Blundell and Bond, 1998). The overall validity of the instruments is tested by a Difference-in-Hansen test of exogeneity of instruments, and the assumption of serially uncorrelated errors is tested using Arellano–Bond AR(1) and AR(2) tests

The long run (dynamic) H statistic is computed as:

$$H = \sum_{j=1}^{3} \beta_j' \tag{A5}$$

Boone indicator (BI). We follow Boone et al. (2005) for a simpler definition of the indicator, and Delis (2012) and Oduro et al. (2022) for an empirical model to estimate it. *BI* is thus defined as a profit elasticity representing the percentage fall in a firm's profit due to a percentage increase in its marginal cost, measured by $\widehat{\beta}$ from this regression:

$$\ln\pi_{it} = \alpha + \beta \ln mc_{it} + \sum_{k=1}^{6} \beta_k \ln Z_{kit} + \sum_{k=7}^{9} \beta_k \ln Z_{kt} + \xi_{it} \tag{A6}$$

where π_i is the profit of each firm i (normalised to positive numbers through linear transformation), mc is the marginal cost (the measure for efficiency), and Z_k is the same vector of nine control variables used in the PR model – here added to control for potential factors that affect the Boone indicator. A time dummy was introduced to control for the financial and sovereign debt crises. Year fixed effects were tried in first instance, but the GMM regression would not converge due to years 2017–2019 being omitted because of collinearity. Hence, a dummy variable crisis was introduced instead, such that crisis = 1 for years 2010–2013, and zero otherwise (year 2014 was the first one with positive real GDP growth)

Since firms' marginal costs cannot be directly observed, Boone et al. (2005) approximate them with average variable costs. These are less complex but less accurate, because we cannot distinguish between variable and fixed costs, so in practice they are often proxied by average costs (Bikker and Van Leuvensteijn, 2008). We use this measure for robustness check only; as first option, we proxy the marginal cost of the FinTech firms from the trans log cost function specified below (Abel and Marire, 2021):

$$\ln(c/w_3) = \alpha_0 + \alpha_1 \ln y + 1/2\alpha_2(\ln y)^2 + \alpha_3 \ln(w_1/w_3) + \alpha_4 \ln(w_2/w_3) + \alpha_5 \ln(w_1/w_3)\ln(w_2/w_3)$$

$$+ 1/2\alpha_6[\ln(w_1/w_3)]^2 + 1/2\alpha_7[\ln(w_2/w_3)]^2 + \alpha_8 \ln y \ln(w_1/w_3) + \alpha_9 \ln y \ln(w_2/w_3) + \varepsilon \tag{A6}$$

The model assumes that the cost function (total cost, c) takes the form of a trans log cost function with one output (y) – representing revenue, R_{it} – and three input prices: of labour (w_1), of fixed capital (w_2), and of financing (w_3). The assumption of linear homogeneity in input prices is imposed by normalising total cost and input prices by one input price. The estimated coefficients of the cost function are then used in the calculation of the marginal cost as the derivative of the logarithm of total cost (c) over output (y):

$$mc = \frac{c}{y}[\alpha_1 + \alpha_2 \ln y + \alpha_8 \ln(w_1/w_3) + \alpha_9 \ln(w_2/w_3)] \tag{A7}$$

To overcome possible endogeneity, we follow Oduro et al. (2022) in estimating the above equations using GMM, with 1-year, 2-year and 3-year lagged values of the explanatory variable, marginal costs, as instrumental variables. Marginal cost tends to weakly correlate with the first difference of the endogenous explanatory variable (Blundell and Bond, 1998). Moreover, if the lagged independent variable has no direct causal impact on the dependent variable nor the unobserved confounder, used as instrumental variable will mitigate the endogeneity problem by reducing bias and the mean squared error (Bellemare et al., 2017). A test for overidentification of the instruments is performed using the Hansen J-test for GMM (Hayashi, 2000).

Lerner index (LI). As defined in the article.

List of firms included in the analysis.

FINTECH	WEB	Details
OWNED		
Bizum	www.bizum.es/	33.4% Caixabank Payments & Consumer EFC (Owned by Caixabank SA), 18.25% Banco Santander, 10.3% Banco Sabadell SA, etc.
Comercia Global Payments	www.comerciaglobalpayments.com/index_es.html	80% Global Payments (US), 20% Caixabank Payments & Consumer EFC (Owned by Caixabank SA)
Euro Automatic Cash	www.euroautomaticcash.es/es/index.html	50% Banco Santander SA, 50% Euro-Information Europeenne (FR)
Imagin	www.caixabank.es/particular/imagin.html#	99.99% Caixabank SA
Instant credit	www.instantcredit.net/	100% Sabadell Innovation Capital (Owned by Banco de Sabadell SA)
MoneyToPay	www.moneytopay.com/	49% Caixabank Payments & Consumer EFC (Owned by Caixabank SA). Direct and indirect control of Caixabank SA: 90%
PagoNxt	www.pagonxt.com/home	99.99% Banco Santander SA
Paycomet	www.paycomet.com/	100% Sabadell Innovation Capital (Owned by Banco de Sabadell SA)
ALLIED		
Card Dynamics	www.es.card-dynamics.com/	ABANCA Innova startup programme (abancainnova.com/bootcamp/attachment/card-dynamics/)
ICO Funding	www.icofunding.com/es/	Alliance with BBVA (tinyurl.com/4z4xh88s)
Toro	www.toro-intl.com/solution	Alliance with Caixabank (toro-intl.com/about-us/)

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FINTECH	WEB	Details
Transferzero	www.azafinance.com/transferzero/	Bankia Fintech startup programme (www.bankiafintech.com/fintech/es/transferzero.html)
Universalpay	www.universalpay.es/	Strategic alliance with Liberbank (tinyurl.com/2p8ehbte)
Wanna	www.wanna.es/	Owned by Fintonic Servicios Financieros SL (Alliance with A3Media & ING Direct: (tinyurl.com/5n8932d9)
Waylet	www.waylet.es/	Owned by Repsol SA (petrochemical). Rounds of financing by Caixa Capital Risc (Criteria) (tinyurl.com/yc6b98m8)
INDEPENDENT		
2gether bank	www.2gether.global/home	No relationship with Spanish banks identified
Adventurees	www.adventurees.com	No relationship with Spanish banks identified
Afterbanks	www.afterbanks.com/	No relationship with Spanish banks identified
Aid & Credit	www.aid-credit.com/	No relationship with Spanish banks identified
alma inversores	www.almainversores.com/	No relationship with Spanish banks identified
Aplazame	www.aplazame.com	No relationship with Spanish banks identified
Arboribus	www.arboribus.com/	No relationship with Spanish banks identified
AvalVida	www.avalvida.es/	No relationship with Spanish banks identified
B&B Financial	www.bybfinancial.com/	No relationship with Spanish banks identified
bankast	www.bankast.com	No relationship with Spanish banks identified
BDKapital	www.bdkapital.es/	No relationship with Spanish banks identified
beenergy	www.beenergypart.com/	No relationship with Spanish banks identified
Besepa	www.besepa.com/	No relationship with Spanish banks identified
Bestaker	www.bestaker.com/	No relationship with Spanish banks identified
BIP&Drive	www.bipdrive.com/	No relationship with Spanish banks identified
Bit2me	www.bit2me.com/inicio	No relationship with Spanish banks identified
Bitnovo	www.bitnovo.com/	No relationship with Spanish banks identified
BMCE Euroservices	www.bmce-intl.com/	No relationship with Spanish banks identified
Bnc 10	www.bnc10.com/	No relationship with Spanish banks identified
Bnext EDE	www.bnext.es/	No relationship with Spanish banks identified
Boletus	www.boletus.com/	No relationship with Spanish banks identified
Borrox	www.borrox.com/	No relationship with Spanish banks identified
Capital Cell	www.capitalcell.es/	No relationship with Spanish banks identified
Circulantis	www.circulantis.com/	No relationship with Spanish banks identified
CivisLend	www.civislend.com/	No relationship with Spanish banks identified
Click Virtual	www.click-virtual.com/	No relationship with Spanish banks identified
Colectual PFP	www.colectual.com	No relationship with Spanish banks identified
Commercegate	www.commercegate.com/	No relationship with Spanish banks identified
Comunitae	www.comunitae.com	No relationship with Spanish banks identified
Crealsa	www.crealsa.es/	No relationship with Spanish banks identified
CrediMarket	www.credimarket.com/	No relationship with Spanish banks identified
Creditea	www.creditea.es/	No relationship with Spanish banks identified
CreditOh!	www.creditoh.com/	No relationship with Spanish banks identified
Creditomas	www.creditomas.es/	No relationship with Spanish banks identified
CreditsGo	www.creditsgo.com	No relationship with Spanish banks identified
Creditstar	www.creditstar.es/	No relationship with Spanish banks identified
cripto pay	www.cripto-pay.com/	No relationship with Spanish banks identified
Crowdants	www.crowdants.com/	No relationship with Spanish banks identified
Crowdcube	www.crowdcube.com/es	No relationship with Spanish banks identified
Crowdence	www.crowdence.com/	No relationship with Spanish banks identified
Crowdfunding Bizkaia	www.crowdfundingbizkaia.com	No relationship with Spanish banks identified
Currencies Direct	www.currenciesdirect.com/es/	No relationship with Spanish banks identified
digital origin	www.digitalorigin.com/	No relationship with Spanish banks identified
Dineo	www.dineo.es/	No relationship with Spanish banks identified
Dinube	www.dinube.com/	No relationship with Spanish banks identified
Dispon.es	www.dispon.es/	No relationship with Spanish banks identified
Easy EP	www.easy-ep.com/	No relationship with Spanish banks identified
EcoCrowdfunding	www.ecocrowdfunding.es	No relationship with Spanish banks identified
Ecrowd!	www.ecrowdinvest.com	No relationship with Spanish banks identified
eInicia	www.einicia.es	No relationship with Spanish banks identified
eKuantia	www.ekuantia.es/	No relationship with Spanish banks identified
elhipotecador	www.elhipotecador.es/	No relationship with Spanish banks identified
Emprestamo	www.emprestamo.com/	No relationship with Spanish banks identified
Envio Dinero	www.enviodinero.es/	No relationship with Spanish banks identified
eSignus	www.esignus.com/	No relationship with Spanish banks identified
Ethic investors	www.ethicinvestors.com/	No relationship with Spanish banks identified
Eurocoin pay	www.eurocoinpay.io	No relationship with Spanish banks identified
Euroloan	www.euroloan.es/	No relationship with Spanish banks identified
Excelend	www.excelend.com	No relationship with Spanish banks identified
Fellow Funders	www.fellowfunders.es/	No relationship with Spanish banks identified
Ferratum Bank	www.ferratum.es/	No relationship with Spanish banks identified
fibanx	www.fibanx.com/	No relationship with Spanish banks identified

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FINTECH	WEB	Details
Filmarket Hub	www.filmarkethub.com/	No relationship with Spanish banks identified
Financlick	www.financlick.es/	No relationship with Spanish banks identified
Finanzarel	www.finanzarel.com/	No relationship with Spanish banks identified
Finergia	www.finergia.es/	No relationship with Spanish banks identified
FinPay	www.finpay.es/	No relationship with Spanish banks identified
Finquietis	www.finquietis.com/	No relationship with Spanish banks identified
Finteca	www.finteca.es/	No relationship with Spanish banks identified
Finweg	www.finweg.com/	No relationship with Spanish banks identified
Flypos	www.flypos.es/	No relationship with Spanish banks identified
Flywire	www.flywire.com/	No relationship with Spanish banks identified
Fuell	www.getfuell.com/es/	No relationship with Spanish banks identified
Fundeen	www.fundeen.com/es	No relationship with Spanish banks identified
GasPay	www.gaspay.com/	No relationship with Spanish banks identified
Gelt Cash	www.geltcash.com/	No relationship with Spanish banks identified
Getneo	www.getneo.com/	No relationship with Spanish banks identified
Grey Systems	www.greysystems.eu/	No relationship with Spanish banks identified
Grow.ly	www.growly.es	No relationship with Spanish banks identified
Housers	www.housers.com/es	No relationship with Spanish banks identified
iAhorro	www.iahorro.com/	No relationship with Spanish banks identified
ibanonline	www.ibanonline.com/es/	No relationship with Spanish banks identified
iCrowdhouse	www.icrowdhouse.com	No relationship with Spanish banks identified
ID Finance	www.idfinance.com/es/	No relationship with Spanish banks identified
IM Solutions (Kineox)	www.kineox.com/en/	No relationship with Spanish banks identified
Inbonis rating	www.inbonis.com/es/	No relationship with Spanish banks identified
Inespay	www.inespay.com/	No relationship with Spanish banks identified
Inmocrowd	www.inmocrowd.es/	No relationship with Spanish banks identified
Inverem	www.inverem.es/	No relationship with Spanish banks identified
Inversa	www.inversa.es/es/	No relationship with Spanish banks identified
Iuvo Group	www.iuvo-group.com/es/	No relationship with Spanish banks identified
iwoca	www.iwoca.es/	No relationship with Spanish banks identified
K apptus	www.kapptus.com/	No relationship with Spanish banks identified
Kantox	www.kantox.com/es/	No relationship with Spanish banks identified
Kapital100	www.kapital100.com/	No relationship with Spanish banks identified
Kaudal	www.kaudal.es/	No relationship with Spanish banks identified
La Bolsa Social	www.bolsasocial.com/	No relationship with Spanish banks identified
Lanzanos	www.lanzanos.com/	No relationship with Spanish banks identified
Lendismart	www.lendismart.com/	No relationship with Spanish banks identified
Lendix	www.es.lendix.com	No relationship with Spanish banks identified
Lendmarket	www.lendmarket.es/	No relationship with Spanish banks identified
Lendrock	www.lendrock.com/	No relationship with Spanish banks identified
Licuos	www.licuos.com/	No relationship with Spanish banks identified
lideralia	www.lideralia.com/	No relationship with Spanish banks identified
Lignum Capital	www.lignumcap.com/	No relationship with Spanish banks identified
Loanbook	www.loanbook.es/	No relationship with Spanish banks identified
Loando	www.loando.es/	No relationship with Spanish banks identified
Marketpay	www.marketpay.io/	No relationship with Spanish banks identified
Microwd	www.microwd.es/	No relationship with Spanish banks identified
Mil Créditos Rápidos	www.milcreditosrapidos.com/	No relationship with Spanish banks identified
MilloLab	www.millolab.com/	No relationship with Spanish banks identified
Monedo	www.monedo.es/	No relationship with Spanish banks identified
Monei	www.monei.net/es/	No relationship with Spanish banks identified
MoneyMan	www.moneyman.com.es/	No relationship with Spanish banks identified
Moneytrans	www.moneytrans.eu/spain/	No relationship with Spanish banks identified
Mychoice 2 pay	www.mychoice2pay.com/es/	No relationship with Spanish banks identified
Mymoid	www.mymoid.com/es/	No relationship with Spanish banks identified
Mynvbest	www.es.mynbest.info/	No relationship with Spanish banks identified
MyTripleA	www.mytripleaprestamos.com	No relationship with Spanish banks identified
Nettit (Ahora Billib)	www.billib.es/	No relationship with Spanish banks identified
Novicap	www.novicap.com/	No relationship with Spanish banks identified
Nowon	www.nowon.es/	No relationship with Spanish banks identified
OK Money	www.okmoney.es/	No relationship with Spanish banks identified
Oney	www.oney.es/	No relationship with Spanish banks identified
Pademobile	www.pademobile.com/esp/	No relationship with Spanish banks identified
Paga+tarde	www.pagamastarde.com	No relationship with Spanish banks identified
Pagaré Direct	www.pagaredirect.es/	No relationship with Spanish banks identified
Pagatelia	www.pagatelia.com/	No relationship with Spanish banks identified
Patrocinalos!	www.patrocinalos.biz/	No relationship with Spanish banks identified
Pay in	www.pay-in.es/	No relationship with Spanish banks identified
Pay in 7	www.payin7.com/	No relationship with Spanish banks identified
Paymatico	www.paymatico.com/	No relationship with Spanish banks identified

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FINTECH	WEB	Details
Paymefy	www.paymefy.com/	No relationship with Spanish banks identified
PaynoPain	www.paynopain.com/	No relationship with Spanish banks identified
PayThunder	www.paythunder.com/	No relationship with Spanish banks identified
Pecunpay	www.pecunpay.es/	No relationship with Spanish banks identified
pepe dinero	www.pepedinero.com/	No relationship with Spanish banks identified
Pleo	www.pleo.io/es	No relationship with Spanish banks identified
Prestalo	www.prestalo.com/	No relationship with Spanish banks identified
Prestamer	www.prestamer.es/	No relationship with Spanish banks identified
Préstamo10	www.prestamo10.com/	No relationship with Spanish banks identified
Prestamos Prima	www.prestamosprima.com/es/inicio.html	No relationship with Spanish banks identified
Prior	www.priorhq.com/	No relationship with Spanish banks identified
Private Investments	www.privateinvestmentsnetwork.com/es/inicio/	No relationship with Spanish banks identified
Propcrowd	www.propcrowd.com/	No relationship with Spanish banks identified
queue no pare la música	www.quenoparelamusica.com	No relationship with Spanish banks identified
Quotanda	www.quotanda.com/es/	No relationship with Spanish banks identified
Rebellion pay	www.rebellionpay.com/	No relationship with Spanish banks identified
Revolupay	www.revolupay.es/	No relationship with Spanish banks identified
RN Tu solución hipotecaria	www.tusolucionhipotecaria.com/	No relationship with Spanish banks identified
Safetypay	www.safetypay.com/es/	No relationship with Spanish banks identified
Savso	www.savso.es/	No relationship with Spanish banks identified
Seed&Click	www.seedandclick.com/	No relationship with Spanish banks identified
Sefide / Momo	www.sefide.com/	No relationship with Spanish banks identified
Sepomo	www.sepomo.com/web/es/	No relationship with Spanish banks identified
Sequra	www.sequra.es/	No relationship with Spanish banks identified
setpay	www.getsetpay.com	No relationship with Spanish banks identified
SiPay	www.sipay.es/	No relationship with Spanish banks identified
small world	www.smallworldfs.com/es/	No relationship with Spanish banks identified
Socilen	www.socilen.com/	No relationship with Spanish banks identified
Socios Inversores	www.sociosinversores.com/	No relationship with Spanish banks identified
Spotcap	www.spotcap.es/	No relationship with Spanish banks identified
Startups Inversores	www.startupsinversores.com/	No relationship with Spanish banks identified
StartupXplore	www.startupxplore.com	No relationship with Spanish banks identified
StockCrowd	www.stockcrowdin.com	No relationship with Spanish banks identified
TefPay	www.tefpay.com/index.php	No relationship with Spanish banks identified
Tesoriza	www.tesoriza.com/	No relationship with Spanish banks identified
The Crowd Angel	www.thecrowdangel.com	No relationship with Spanish banks identified
Trocobuy	www.trocobuy.com/es	No relationship with Spanish banks identified
TropiPay	www.tropipay.com/	No relationship with Spanish banks identified
Tu Finanziacion	www.tufinanziacion.com/	No relationship with Spanish banks identified
Twinero	www.twinero.es/	No relationship with Spanish banks identified
United Food Republic	www.unitedfoodrepublic.com/	No relationship with Spanish banks identified
Up Aganea	www.up-aganea.com/	No relationship with Spanish banks identified
Urbanitae	www.urbanitae.com	No relationship with Spanish banks identified
Verse	www.verse.me/es/	No relationship with Spanish banks identified
viaconto	www.viaconto.es/	No relationship with Spanish banks identified
Vivus.es	www.vivus.es/	No relationship with Spanish banks identified
WayApp	www.wayapp.com	No relationship with Spanish banks identified
WayApp Pay	www.pay.wayapp.com	No relationship with Spanish banks identified
We Tech	www.wetech.es/es/home/	No relationship with Spanish banks identified
Wecity	www.wecity.io/es/	No relationship with Spanish banks identified
Welp	www.welponline.com/es/	No relationship with Spanish banks identified
Winvestify	www.winvestify.com/	No relationship with Spanish banks identified
Woonivers	www.woonivers.com/	No relationship with Spanish banks identified
Worldcoo	www.worldcoo.com/es/	No relationship with Spanish banks identified
Zank	www.zank.com.es	No relationship with Spanish banks identified

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